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Lecue et al.

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(54) **ENHANCED IMAGE OBJECT DETECTION USING SEMANTIC KNOWLEDGE GRAPH AUGMENTATION**

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G06N 3/042	(2023.01)
G06N 3/08	(2023.01)
G06V 10/82	(2022.01)
G06V 30/19	(2022.01)
G06V 30/262	(2022.01)
G06V 20/58	(2022.01)

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CPC ***G06V 10/454*** (2022.01); ***G06F 16/9024*** (2019.01); ***G06N 3/042*** (2023.01); ***G06N 3/08*** (2013.01); ***G06V 10/82*** (2022.01); ***G06V 30/19173*** (2022.01); ***G06V 30/274*** (2022.01); *G06V 20/58* (2022.01)

(58) **Field of Classification Search**
None
See application file for complete search history.

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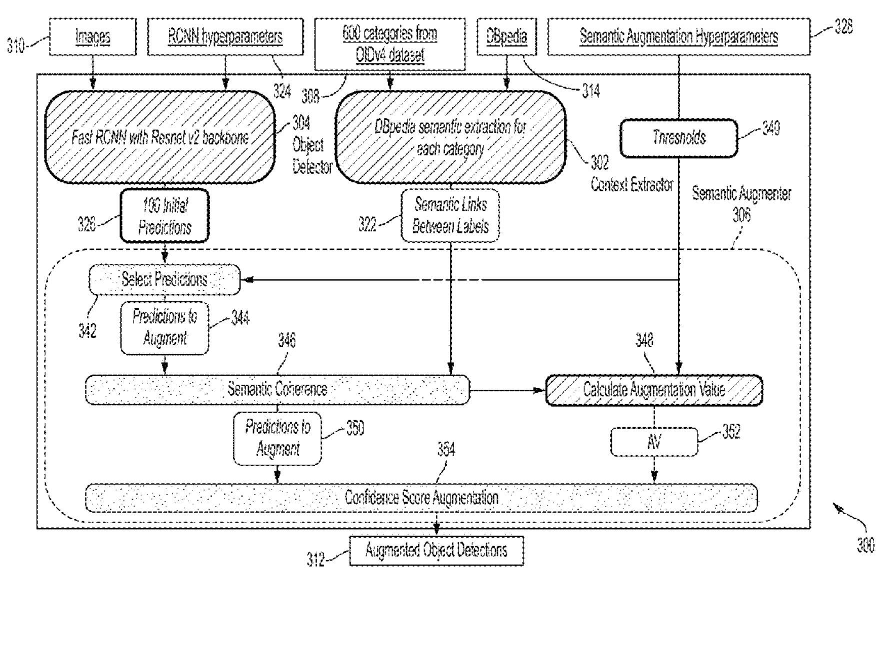
(57) **ABSTRACT**

A method of semantic object detection in an image dataset includes extracting semantic links relevant to the image dataset. Objects are detected in the image dataset and confidence scores are assigned to the detected objects. The semantic object detection compares the detected objects with the semantic links and augments the confidence scores based on the semantic links between the detected objects.

20 Claims, 5 Drawing Sheets



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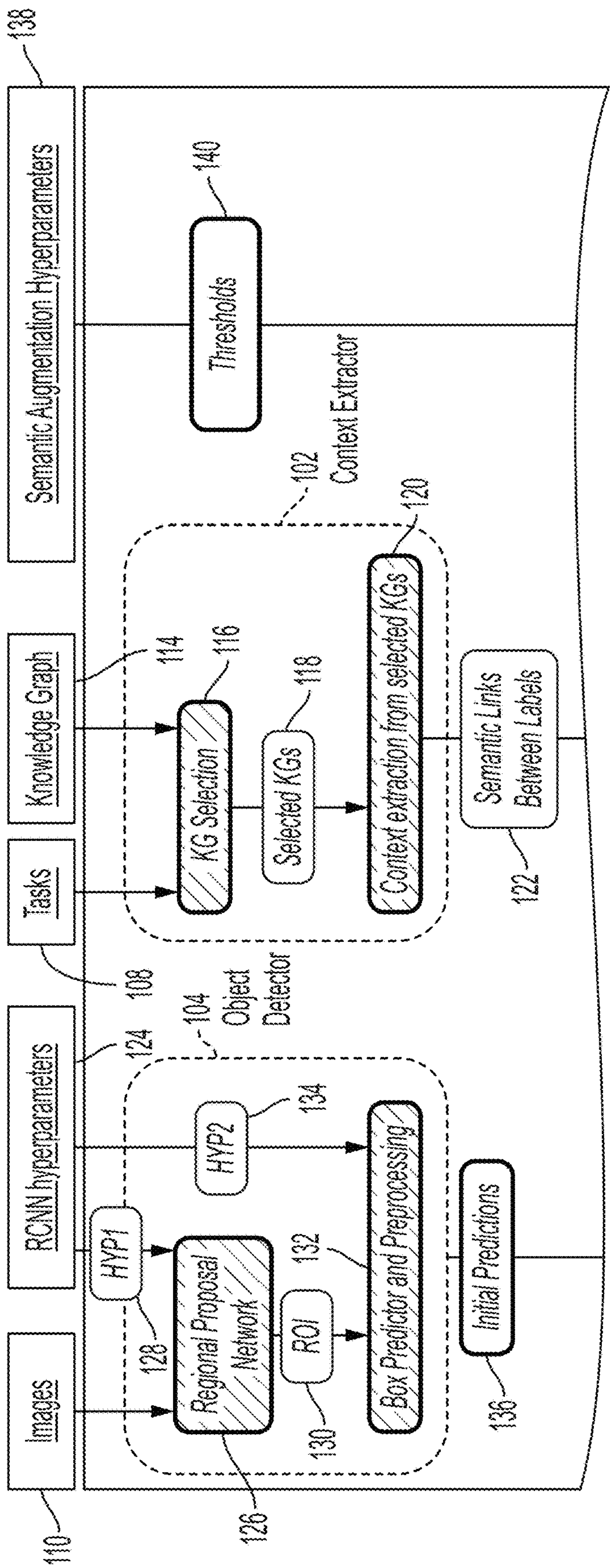

TO FIG. 1B

FIG. 1A

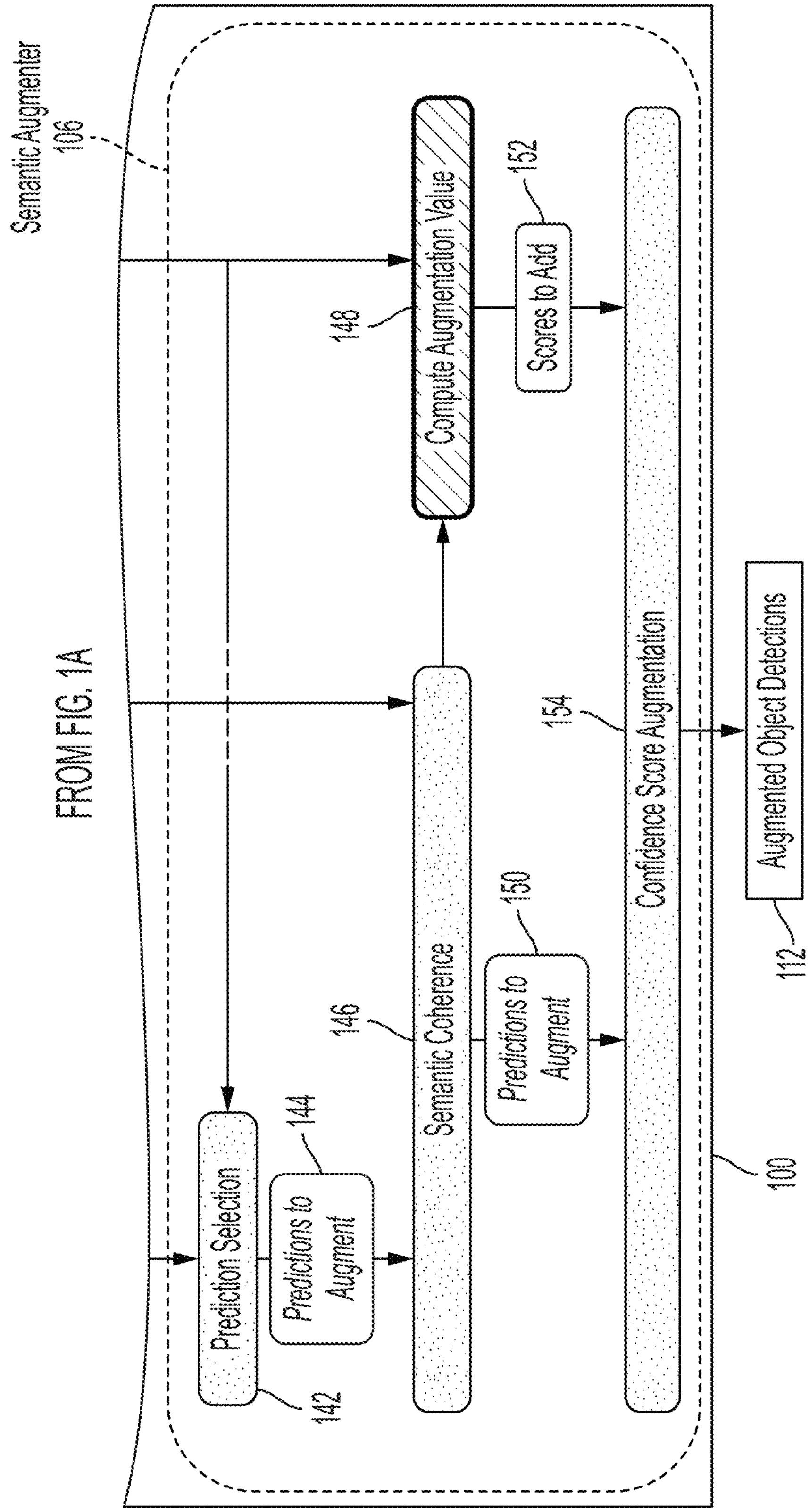
FROM FIG. 1A
Semantic Augmenter
106
Prediction Selection
142
Predictions to Augment
144
Semantic Coherence
146
Predictions to Augment
150
Compute Augmentation Value
148
Scores to Add
152
Confidence Score Augmentation
154
Augmented Object Detections
112
100

FIG. 1B

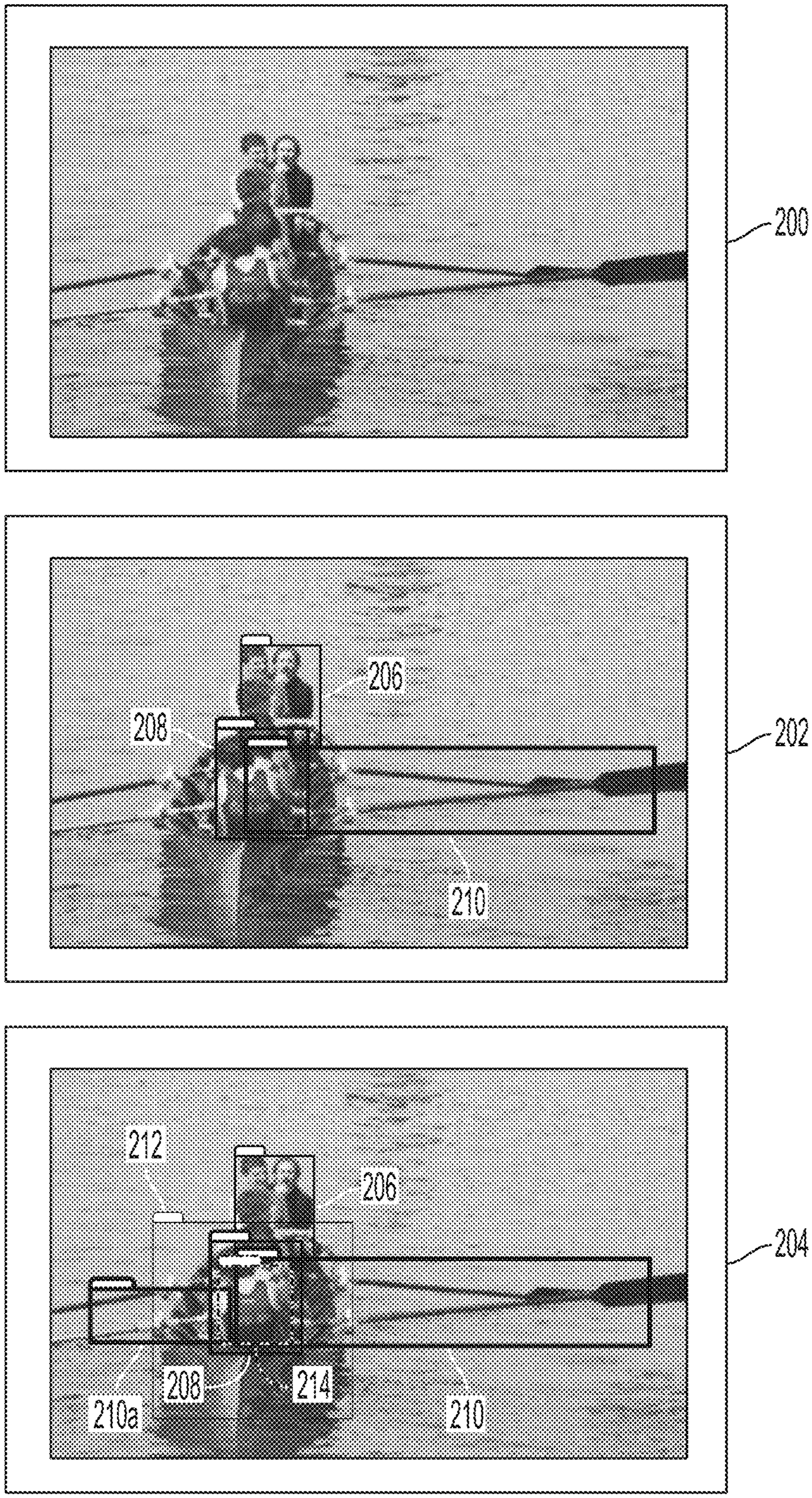

FIG. 2

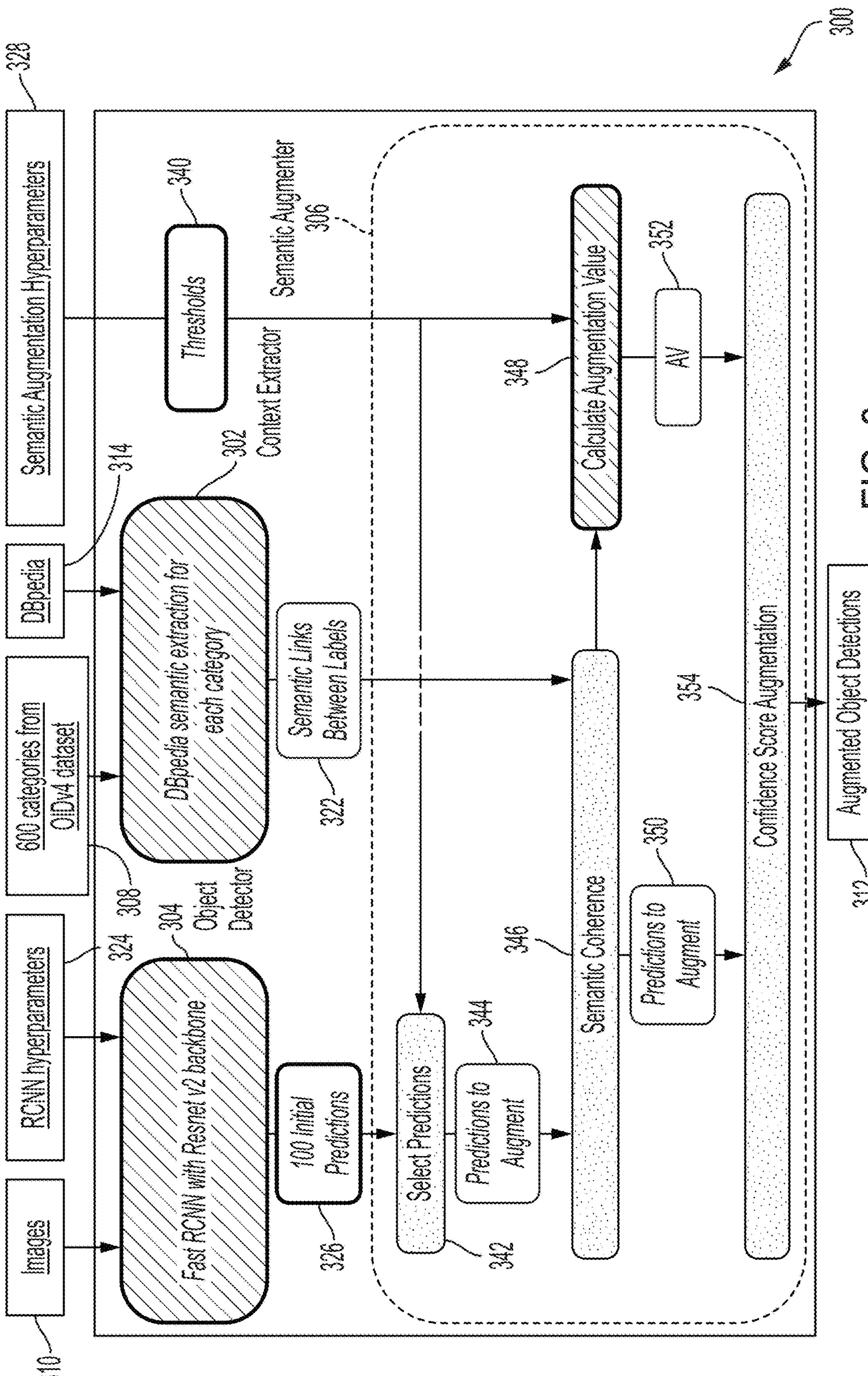
300
Images
310
RCNN hyperparameters
324
600 categories from OIDv4 dataset
308
DBpedia
314
Semantic Augmentation Hyperparameters
328
Fast RCNN with Resnet v2 backbone
304
Object Detector
DBpedia semantic extraction for each category
302
Context Extractor
Thresholds
340
Semantic Augmenter
306
100 Initial Predictions
326
Semantic Links Between Labels
322
Select Predictions
342
Predictions to Augment
344
Semantic Coherence
346
Calculate Augmentation Value
348
Predictions to Augment
350
AV
352
Confidence Score Augmentation
354
Augmented Object Detections
312

FIG. 3

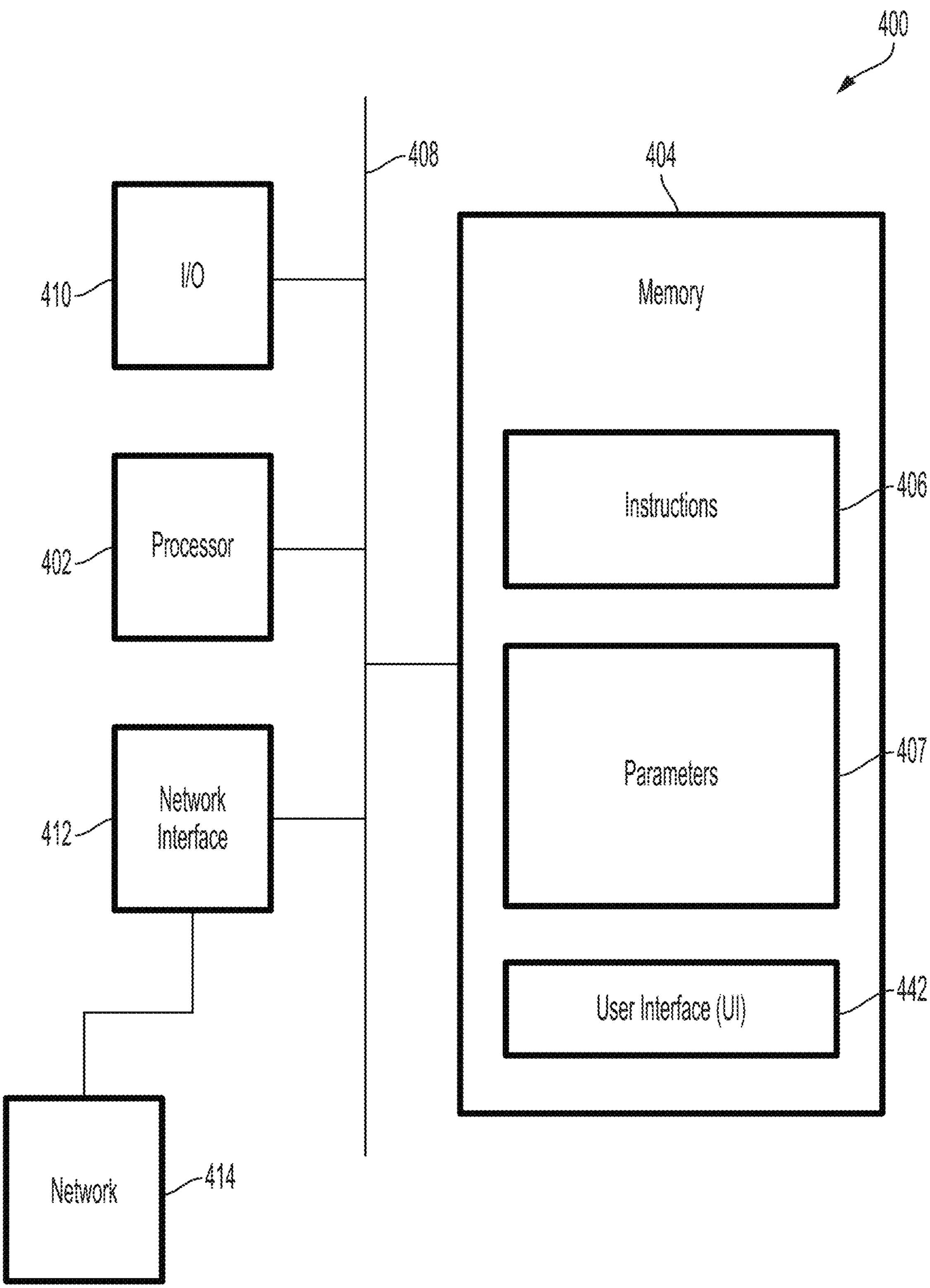
400
408
404
I/O
410
Memory
Instructions
406
Processor
402
Parameters
407
Network
Interface
412
User Interface (UI)
442
Network
414

FIG. 4

ENHANCED IMAGE OBJECT DETECTION USING SEMANTIC KNOWLEDGE GRAPH AUGMENTATION

PRIORITY CLAIM AND CROSS-REFERENCE

The present application claims the priority benefit of U.S. Provisional Patent Application No. 62/980,657, filed Feb. 24, 2020, the entirety of which is hereby incorporated by reference.

BACKGROUND

Object detection processes locate the presence of objects using a bounding box and types or classes of the located objects in an image. Object detection processes receive as input an image with one or more objects, such as a photograph and output one or more bounding boxes, a class label for each bounding box and a confidence score.

Deep Neural Networks (DNN) perform well on a variety of pattern-recognition tasks, such as semantic segmentation and visual classification. DNNs rely on sophisticated machine learning models trained on massive datasets with respect to scalable, high-performance infrastructures, creating and using decision systems that are not rationally explainable. In particular, DNNs do not apply context and semantic relationships between objects to make identifications.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is a flowchart of a semantic object detection method, in accordance with some embodiments.

FIG. **2** is a series of images depicting semantic augmentation, in accordance with an embodiment.

FIG. **3** is a flowchart of a semantic object detection method, in accordance with some embodiments.

FIG. **4** is a high-level block diagram of a processor-based system usable in conjunction with one or more embodiments.

DETAILED DESCRIPTION

The following disclosure provides many different embodiments, or examples, for implementing different features of the provided subject matter. Specific examples of components, values, operations, materials, arrangements, or the like, are described below to simplify the present disclosure. These are, of course, merely examples and are not intended to be limiting. Other components, values, operations, materials, arrangements, or the like, are contemplated. For example, the formation of a first feature over or on a second feature in the description that follows may include embodiments in which the first and second features are formed in direct contact and may also include embodiments in which additional features may be formed between the first and second features, such that the first and second features may not be in direct contact. In addition, the present disclosure may repeat reference numerals and/or letters in the various examples. This repetition is for the purpose of simplicity and clarity and does not in itself dictate a relationship between the various embodiments and/or configurations discussed.

Further, spatially relative terms, such as "beneath," "below," "lower," "above," "upper" and the like, may be used herein for ease of description to describe one element or feature's relationship to another element(s) or feature(s) as illustrated in the figures. The spatially relative terms are intended to encompass different orientations of the device in use or operation in addition to the orientation depicted in the figures. The apparatus may be otherwise oriented (rotated 90 degrees or at other orientations) and the spatially relative descriptors used herein may likewise be interpreted accordingly.

FIG. **1** is a flowchart of an augmented object detection method **100**, in accordance with an embodiment.

The context extractor **102** receives object detection tasks **108** including expected labels for the objects which the object detection task **108** expects to detect. For example, the object detection tasks **108** may be tasks related to train operation and safety and some of the expected objects may be signals, signs and other common wayside objects. Example of objects detection tasks are obstacle detection in front of an operating vehicle e.g., train, car, boat, submarine, drone or plane; detecting abnormal situations where particular objects might be detected in the context of security in city, airport, train, manufacturing plants.

A knowledge graph selection module **116** processes the object detection tasks **108** to determine the expected labels found for the object detection task and selects appropriate knowledge graphs **118** from the available knowledge graphs stored in a knowledge graph database **114** by selecting the knowledge graphs **118** that include the expected labels.

A label is a word that signifies an object, a class of objects, a category of objects or a component of an object. For example "PERSON", "MAN", "BOAT" and "NOSE" are labels.

A knowledge graph **114** is a database of labels and semantic links. A semantic link **122** defines the relationships between objects represented by labels. For example, the semantic link ""NOSE" is a part of "FACE"" defines the relationship between a nose and a face.

A knowledge graph database **114** catalogs semantic links between labels (objects, concepts and categories). The semantic links relate the objects, concepts and categories to each other. When objects are identified in an image and those objects are semantically linked, confidence in the accuracy of the identification is enhanced because the identification is supported by a human-understandable causality.

Knowledge graph databases **114** are selected according to their relevancy to the expected objects, concepts and categories of the object detection task.

For the expected labels associated with the object detection tasks **108**, a context extraction module **120** extracts and outputs the semantic links **122** associated with the expected labels.

The object detector **104** is a trained machine learning algorithm, such as a DNN, Region-Based Convolutional Neural Network (RCNN), or other appropriate neural network. RCNN are a family of techniques for addressing object localization and recognition tasks, designed for model performance.

In accordance with an embodiment, object detector **104** is a programmed neural network that receives images **110** as inputs and outputs initial predictions **136** of object identifications including labels, bounding boxes and confidence scores.

A bounding box is a set of spatial coordinates defining the space in an image that contains an identifiable object.

A confidence score is an assessment (0-100%) of an identification by the object detector based on the historical success of previous identifications.

A region proposal network **126** analyzes the images to generate and select proposed regions of interest (ROI) **130**.

Region proposal network **130** receives images **110** as input and identifies ROI **130** defining regions of the images that contain identifiable objects. The number of region proposals **130** output is set by optimized hyperparameters (HYP1) **128**.

RCNN Hyperparameters **124** and Semantic Augmentation Hyperparameters **138** are parameters applied to the object detection and augmentation processes to set thresholds of confidence scores for detection and to the number of outputs for the searches. in at least one embodiment for example, a detection is made with a confidence score of 40% and the top 100 detections are returned as initial object predictions **136**. The hyperparameters **128**, **134** and **140** are optimized for a given object detection task by running test data and varying the hyperparameters to return a maximum number of detections and minimizing the number of false positive detections.

The region proposals **130** are further analyzed to identify initial object predictions **136** by a box predictor and preprocessing module **132**. The box predictor and preprocessing module **132** is a programmed neural network that identifies initial predictions **136** including bounding boxes within the ROI, labels and confidence scores.

The initial predictions **136** are processed by the semantic augmenter **206**. The confidence scores of the initial predictions **136** are compared to the thresholds **140**. When the confidence score of initial predictions **136** are greater than the threshold **140**, a prediction selection module **142** selects those initial predictions to augment **144**. A higher threshold returns fewer detections for processing. A lower threshold returns more detections for processing. The threshold **140** is 40%, in accordance with an embodiment. Comparing the labels of the predictions to augment **144** with the semantic links between labels **222** generated by the context extractor **202**, a semantic coherence module **146** determines which identifications are supported by the presence of labels that are semantically linked.

When the labels in the predictions to augment **144** are semantically linked, an augmentation value **152** is calculated by a Compute Augmentation Value module **148**. The augmentation value **152** is calculated based on the number of semantic links **122** and thresholds **140**.

A confidence score augmentation module receives the predictions to augment **150** from the semantic coherence module **146** and the augmentation value **152** from the compute augmentation value module **148** and augments the confidence score of the predictions to augment **150** by adding the augmentation value **152** to the confidence score. The predictions to augment **150** with augmented confidence scores are output as augmented object detections **112**.

An augmented object detection **112** is an object detection with a confidence score that has been increased when semantic links **122** found in a knowledge graph **214** correspond to the identified objects. For example, supposing an image resulted in detections of both a "PADDLE" and a "BOAT", the confidence scores of both detections would be increased to reflect the semantic link "PADDLE" is an accessory of "BOAT" found in a knowledge graph.

FIG. **2** is a series of images depicting semantic augmentation, in accordance with an embodiment.

An object detection task is the detection of one or more objects and the identification of those objects. The objects are classified conceptually by categories from a finite set of categories. An object detector, such as object detector **104** in FIG. **1** analyzes an image **200** or sequence of images. As shown in image **102**, the object detector **104** generates bounding boxes **206**, **208** and **210** corresponding to initial predictions **136** identified in the image. The object detector uses a programmed neural network to find patterns within the image data that corresponds to previously identified objects defined spatially by a bounding box and a confidence score, the percentage of time such an identification has historically been correct. In this example, bounding box **206** is identified as "MAN". Bounding box **208** is identified as "PERSON". Bounding box **210** is identified as "PADDLE". The neural network determines a confidence score for each identification. As an example, "MAN" was identified with a confidence score of 46%, "PERSON" was identified with a confidence score of 66%, and "PADDLE" was identified with a confidence score of 50%. These three detections were returned because the threshold set by hyperparameter HYP2 **134** is set at 40% and so only detections with a confidence score above 40% are output.

The reasoning for the identifications is embedded in the programming and generally cannot be explained to a person. The confidence scores provided by the object detector **104** reflect the programming of the neural network and not the context of the scene represented by the image.

By taking context into account, an augmented object detection method **100** uses semantic information relating detected objects to augment the confidence score. The confidence scores of all initial predictions **136** are augmented when semantic links are identified between the detections. Further objects are detected when confidence scores are augmented and are above the threshold. As shown in image **204**, the augmented object detection has identified additional bounding boxes **210***a*, **212** and **214**. After augmentation, bounding box **206** is identified as "MAN" with a confidence score of 56%, bounding box **208** is identified as "PERSON" with a confidence score of 66%, bounding boxes **210** and **210***a* are identified as "PADDLE" with a confidence score of 74%, bounding box **212** is identified as "BOAT" with a confidence score of 58% and bounding box **214** is identified as "LIFEJACKET" with a confidence score of 52%. In this example, the presence of paddles increases the confidence in the detection of a boat, a second paddle and a lifejacket. The detection of a person and a boat increases the confidence in the detection of a man. The increased confidence in the detections allows systems using the output to place an increased reliance on the object detections. The presence of semantic links between identified objects is a reasonable explanation for accepting an object detection as valid.

FIG. **3** is a flowchart of an augmented object detection system and method **300**, in accordance with an embodiment. The augmented object detection method **300** includes a context extractor **302**, an object detector **304** and a semantic augmenter **306**. The augmented object detection method **300** receives object detection tasks **308**, for example categories from a dataset, and images **310** and outputs augmented object detections **312**.

The Open Image Dataset (https://arxiv.org/abs/1811.00982) released by Google (OIDv4) is the largest existing dataset with object location annotation, containing 15.4 M bounding-boxes for 600 categories on 1.9 M images (2 M have been hand annotated). The dataset provides the granularity needed to assess global coherency of a detected scene.

Training of the neural network for the object detector **304** on this dataset is performed using a pre-trained detection model. Among the pretrained models on OIDv4 available online, the Faster RCNN with ImageNet pre-trained Inception Resnet v2 provides a compromise between detection performance and speed.

The context extractor **302** receives object detection tasks **308** including labels corresponding to expected objects for detection. Using semantic information from DBpedia **314**, the context extractor **302** extracts semantic information for each category and label and outputs the semantic links **322** between the labels.

The knowledge graphs **314** used for semantic context extraction include, in accordance with an embodiment, DBpedia (https://wiki.dbpedia.org/) is an efficient graph to extract a unique resource for the 600 categories (95% of coverage).

In accordance with an embodiment, the object detector **304** is a Faster RCNN with Resnet v2 backbone. Using RCNN hyperparameters **324** such as threshold limits, the object detector **304** identifies **100** initial object predictions **326**.

The **100** initial object predictions **336** are processed by the semantic augmenter **306**. Comparing semantic augmentation hyperparameters **338** such as thresholds **340**, a select predictions module selects predictions to augment **344**. Using the semantic links between labels **322** generated by the context extractor **302**, a semantic coherence module **346** compares the predictions to augment **344** with the semantic links between labels **322**.

When semantic links are identified between the labels of the predictions to augment **344**, a calculate augmentation value module **348** calculates an augmentation value (AV) **352** using the number of semantic links and thresholds **340**. The augmentation value is added to the confidence scores of the predictions to augment **350** at the confidence score augmentation module **354**. The confidence score augmentation module **354** outputs augmented object detections **312**.

The method semantically interprets objects in data, e.g., identifying an object as a car because the object has been identified as a vehicle with four wheels, windows, on a road, with people inside, or the like. A structured database, such as a knowledge graph, is used to correlate objects that compose the scene, and to extract a logical picture of the object interrelations.

The configuration of the faster-RCNN includes a region proposal network of 100 regions, with non-max suppression intersection over union (IoU) threshold at confidence score 0.7 to limit duplicate region detection, and no non-max suppression score threshold, so all regions are used in the non-max suppression. Then the second stage of the RCNN infers detections for these 100 regions, with no additional non-max suppression, so any duplicate regions are treated as unique. These 100 bounding boxes with detected classes are the **100** initial predictions **336**.

Hyper-parameters, optimized during training, define thresholds. Detections with a confidence score less than a threshold are not augmented and do not contribute to confidence augmentation of another detection.

For each prediction with an initial score higher than the threshold, an augmented value **352** is derived. The augmented value **352** indicates if the contexts, i.e., the other detections on the image, are coherent with the detected category according to the semantic links between labels **322** extracted from DBpedia **314**. The list of linked labels in semantic links between labels **322** are consulted. A check is made to determine if each linked label has been detected in the image **310** with a confidence score higher than the threshold. If a linked label is determined to have been detected in the image, the confidence score is added to the trustworthy indicator. If a linked label is determined not to have been detected in the image, the confidence score for that detection is not changed or is reduced. For each label detected, the linked labels are checked and the confidence score of the detection is augmented for each linked label also detected.

The augmented value **352** is compared to a predefined trustworthy threshold **340**.

If the augmented value **352** is less than the trustworthy threshold **340**, the initial detection score is unchanged or is reduced. The context does not bring more confidence about the detection.

If the augmented value **352** is higher than the trustworthy threshold **340**, the initial detection score is augmented at step **354**. To derive the score to add **352**, the same indicator is computed as in the first step but does not include contributions where the augmented value **352** did not reach the trustworthy threshold **340** in the first step. This prevents bad predictions from resulting in an increase of confidence.

FIG. **4** is a block diagram of an object detection system **400**, in accordance with some embodiments. In at least some embodiments, object detection system **400** performs augmented object detection method **100**.

In some embodiments, object detection system **400** is a general purpose computing device including a hardware processor **402** and a non-transitory, computer-readable storage medium **404**. Storage medium **404**, amongst other things, is encoded with, i.e., stores, computer program code **406**, i.e., a set of executable instructions. Execution of instructions **406** by hardware processor **402** represents (at least in part) an object detection tool which implements a portion or all of the methods described herein in accordance with one or more embodiments (hereinafter, the noted processes and/or methods).

Processor **402** is electrically coupled to computer-readable storage medium **404** via a bus **408**. Processor **402** is also electrically coupled to an I/O interface **410** by bus **408**. A network interface **412** is also electrically connected to processor **402** via bus **408**. Network interface **412** is connected to a network **414**, so that processor **402** and computer-readable storage medium **404** are capable of connecting to external elements via network **414**. Processor **402** is configured to execute computer program code **406** encoded in computer-readable storage medium **404** in order to cause system **400** to be usable for performing a portion or all of the noted processes and/or methods. In one or more embodiments, processor **402** is a central processing unit (CPU), a multi-processor, a distributed processing system, an application specific integrated circuit (ASIC), and/or a suitable processing unit.

In one or more embodiments, computer-readable storage medium **404** is an electronic, magnetic, optical, electromagnetic, infrared, and/or a semiconductor system (or apparatus or device). For example, computer-readable storage medium **404** includes a semiconductor or solid-state memory, a magnetic tape, a removable computer diskette, a random access memory (RAM), a read-only memory (ROM), a rigid magnetic disk, and/or an optical disk. In one or more embodiments using optical disks, computer-readable storage medium **404** includes a compact disk-read only memory (CD-ROM), a compact disk-read/write (CD-R/W), and/or a digital video disc (DVD).

In one or more embodiments, storage medium **404** stores computer program code **406** configured to cause system **400** to be usable for performing a portion or all of the noted processes and/or methods. In one or more embodiments, storage medium **404** also stores information which facilitates performing a portion or all of the noted processes and/or methods. In one or more embodiments, storage medium **404** stores parameters **407**.

Object detection system **400** includes I/O interface **410**. I/O interface **410** is coupled to external circuitry. In one or more embodiments, I/O interface **410** includes a keyboard, keypad, mouse, trackball, trackpad, touchscreen, and/or cursor direction keys for communicating information and commands to processor **402**.

Object detection system **400** also includes network interface **412** coupled to processor **402**. Network interface **412** allows system **400** to communicate with network **414**, to which one or more other computer systems are connected. Network interface **412** includes wireless network interfaces such as BLUETOOTH, WIFI, WIMAX, GPRS, or WCDMA; or wired network interfaces such as ETHERNET, USB, or IEEE-1364. In one or more embodiments, a portion or all of noted processes and/or methods, is implemented in two or more systems **400**.

Object detection system **400** is configured to receive information through I/O interface **410**. The information received through I/O interface **410** includes one or more of instructions, data, design rules, libraries of standard cells, and/or other parameters for processing by processor **402**. The information is transferred to processor **402** via bus **408**. Object detection system **400** is configured to receive information related to a UI through I/O interface **410**. The information is stored in computer-readable medium **404** as user interface (UI) **442**.

In some embodiments, a portion or all of the noted processes and/or methods is implemented as a standalone software application for execution by a processor. In some embodiments, a portion or all of the noted processes and/or methods is implemented as a software application that is a part of an additional software application. In some embodiments, a portion or all of the noted processes and/or methods is implemented as a plug-in to a software application.

In some embodiments, the processes are realized as functions of a program stored in a non-transitory computer readable recording medium. Examples of a non-transitory computer readable recording medium include, but are not limited to, external/removable and/or internal/built-in storage or memory unit, e.g., one or more of an optical disk, such as a DVD, a magnetic disk, such as a hard disk, a semiconductor memory, such as a ROM, a RAM, a memory card, and the like.

The foregoing outlines features of several embodiments so that those skilled in the art may better understand the aspects of the present disclosure. Those skilled in the art should appreciate that they may readily use the present disclosure as a basis for designing or modifying other processes and structures for carrying out the same purposes and/or achieving the same advantages of the embodiments introduced herein. Those skilled in the art should also realize that such equivalent constructions do not depart from the spirit and scope of the present disclosure, and that they may make various changes, substitutions, and alterations herein without departing from the spirit and scope of the present disclosure.

What is claimed is:

1. A method of augmented semantic object detection in an image dataset comprising:

receiving an object detection task including expected labels;

selecting a knowledge graph that includes the expected labels;

extracting semantic links relevant to the image dataset with the knowledge graph;

detecting objects in the image dataset using a regional proposal network;

determining initial predictions of detected objects, where the initial predictions of detected objects have confidence scores;

comparing the confidence scores of the initial predictions of detected objects with a threshold;

selecting detected objects from the initial predictions of detected objects for augmentation;

comparing the selected detected objects with the semantic links; and

augmenting the confidence scores based on the semantic links between the detected objects.

2. The method of claim **1**, wherein extracting semantic links is performed by comparing expected labels from the object detection task with the knowledge graph to extract the semantic links for the expected labels.

3. The method of claim **2**, wherein the detected objects have detected object labels and semantic links between the detected object labels are identified from the semantic links for the expected labels.

4. The method of claim **3**, wherein the confidence scores are augmented for each semantic link identified between detected objects.

5. The method of claim **1**, wherein detecting objects in the image dataset is performed using a trained neural network.

6. The method of claim **1**, further comprising assessing the coherency by comparing the detected objects with semantic information from the knowledge graph.

7. The method of claim **1**, wherein the confidence score is increased for each object detection that is semantically linked.

8. An augmented semantic object detection system comprising:

a context extraction module receiving an object detection task including expected labels, selecting a knowledge graph data base that includes the expected labels based on the object detection task and extracting semantic links relevant to the object detection task from the knowledge graph database;

an object detection module receiving an image dataset and using a regional proposal network;

determining initial predictions of detected objects, where the initial predictions of detected objects have confidence scores;

comparing the confidence scores of the initial predictions of detected objects with a threshold;

selecting detected objects from the initial predictions of detected objects for augmentation; and

a semantic augmentation module receiving the selected detected object, object detection confidence scores, and the extracted semantic links and augments the object detection confidence scores based on correlations between the object detections and the extracted semantic links.

9. The semantic object detection system of claim **8** wherein the object detection task includes expected labels and the semantic links are semantic links between the expected labels.

10. The semantic object detection system of claim **9**, wherein the object detections include object detection labels corresponding to detected objects.

11. The semantic object detection system of claim **10**, wherein the correlations are based on comparisons of the expected labels that are semantically linked and the detected object labels.

12. The semantic object detection system of claim **8** wherein the object detection module is a neural network.

13. The semantic object detection system of claim 9 wherein the knowledge graph database is DBpedia.

14. The semantic object detection system of claim 8 wherein the object detection module outputs object detections and object detection confidence scores when the object detection confidence scores exceed a threshold.

15. A method of augmented semantic object detection in an image dataset comprising:

receiving an object detection task including expected labels;

selecting a knowledge graph database based on an object detection task including expected labels;

extracting semantic links between the expected labels from the knowledge graph database;

processing an image dataset to generate object detections and object detection confidence scores using a regional proposal network;

determining initial predictions of detected objects, where the initial predictions of detected objects have confidence scores;

comparing the confidence scores of the initial predictions of detected objects with a threshold;

selecting detected objects from the initial predictions of detected objects for augmentation;

comparing the selected detected objects to the extracted semantic links between expected labels;

updating the object detection confidence scores based on the comparison of the object detections to the extracted semantic links.

16. The method of claim 15, wherein said object detection task includes comparing the object detection confidence score to a threshold and comparing the object detections to the extracted semantic links between expected labels when the confidence score is greater than the threshold.

17. The method of claim 15, wherein the object detection confidence score is increased for each object detection that is semantically linked.

18. The method of claim 15, wherein the knowledge graph database selection is performed by comparing the object detection labels with expected labels in the knowledge graph database.

19. The method of claim 15, wherein the object detection confidence score is unchanged when an object detection is not semantically linked.

20. The method of claim 17, wherein an increase in an object detection confidence score increases other object detection confidence scores.

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